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Supporting the students most in need: Academic self-efficacy and perceived teacher support in relation to within-year academic growth[☆]

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ABSTRACT

Academic self-efficacy and perceived teacher support in relation to academic skill growth across one academic year were examined in the study. Participants included 193 5th-grade students. Teachers collected curriculum-based measures (CBM) of reading and math on three occasions as part of routine academic benchmarks, and researchers collected student-reported measures of academic self-efficacy and perceived teacher support in the spring of the same academic year. Results indicated that academic self-efficacy was positively related to fall reading and math CBM scores and that perceived teacher support was unrelated to fall scores or growth across the academic year. Academic self-efficacy and perceived teacher support interacted in relation to math CBM growth such that low levels of perceived teacher support were related to greater growth, particularly for students with high academic self-efficacy. Follow-up analyses indicated that students with the lowest fall CBM scores and smallest growth rates reported higher levels of perceived teacher support, suggesting that teachers support the students most in need.

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1. Introduction

Although a variety of motivation-related beliefs have been linked to academic achievement (Linnenbrink & Pintrich, 2002), much less is known regarding how perceived teacher support interacts with these beliefs to influence learning outcomes. Both academic self-efficacy (Pajares, 1996; Pintrich & Schunk, 2002) and perceived teacher support (Malecki & Demaray, 2003) relate to higher academic achievement. Perceived teacher support appears to be particularly important for students at risk for academic failure (Baker, 1999; Elias & Haynes, 2008; Malecki & Demaray, 2006); consequently, perceived teacher support may be more important for students with low academic self-efficacy. The purpose of this study is to explore this possibility by examining academic self-efficacy and perceived teacher support in relation to within-year growth in reading and mathematics in 5th-grade students.

1.1. Academic self-efficacy

Academic self-efficacy represents an individual's confidence that he or she can successfully execute academic tasks at selected levels, based on abilities, attitudes, and previous experiences (Lorsbach & Jinks, 1999; Schunk, 1991). With high academic self-efficacy, individuals tend to approach difficult tasks and activities readily (Pajares, 1996; Schunk, 1991). In contrast, students with low academic self-efficacy tend to give up on a learning process when early efforts do not result in perceived or actual success (Schunk, 1984). Low academic self-efficacy can lead to less academic engagement, which could lead to lower success, further reducing academic self-efficacy (Lorsbach & Jinks, 1999).

Academic self-efficacy has been linked to a variety of achievement-related outcomes, including grade point average (GPA), standardized test scores, persistence on difficult tasks, and enrollment in challenging courses (see Pajares, 1996; Pintrich & Schunk, 2002). The robustness of findings across different age groups and academic subjects led Pajares (1996) to describe the link between academic self-efficacy and academic performance as “reasonably secured” (p. 563). Despite the extensive research on academic self-efficacy, social contextual factors such as perceived teacher support that could modify the relation between academic self-efficacy and academic performance are largely unexplored.

1.2. Perceived teacher support

A variety of studies have found that perceptions of supportive relations with teachers are related to greater academic achievement, higher levels of student engagement, less problem behavior, and more positive peer relations (e.g., Birch & Ladd, 1997; Hamre & Pianta, 2001; Skinner, Furrer, Marchand, & Kindermann, 2008). Despite conceptualization of teacher–student relationships as involving (a) teachers' perceptions of students, (b) students' perceptions of teachers, and (c) the observable social interactions between teachers and students (Pianta, 1999), researchers tend to emphasize and measure only one of these components in individual studies. For example, the majority of studies on teacher–student relationships have relied on teacher reports of support (e.g., Birch & Ladd, 1997; Hamre & Pianta, 2001; Skinner et al., 2008), some have included student perceptions of teacher support (e.g., Demaray & Malecki, 2002; Dubow, Tisak, Causey, Hryshko, & Reid, 1991), and very few have included observations of actual supportive interactions in the classroom (e.g., Hamre & Pianta, 2005).

In general, positive relations between teacher support and student outcomes have been found across studies regardless of the operationalization of support; however, some researchers have argued that students' perceptions of support may be better predictors of psychological adjustment and resiliency than actual levels of support (Cohen & Wills, 1985; Murray, Murray, & Waas, 2008). For these reasons, we chose to focus on students' perceptions of teacher support in the current study.

Broad social support consists of four subtypes: emotional, instrumental, informational, and appraisal support (House, 1981). Emotional support includes feelings of empathy, concern, and trust. Instrumental support consists of direct intervention by spending time with someone and providing assistance, materials, and help. Informational support is providing someone with verbal directions, advice, or suggestions. Appraisal support consists of providing someone with affirmation and evaluative feedback. House's (1981) conceptualization of support is frequently used in studies on perceived teacher support (e.g., Malecki & Demaray, 2003) and is the conceptualization used in the current study.

1.3. Relation between perceived teacher support and academic performance

In general, research has revealed a relatively consistent positive relation between perceived teacher support and academic performance; however, some evidence suggests that perceived teacher support may be more beneficial for low performing students than for higher performing students. Thus, perceived teacher support could be a particularly important factor to consider when studying students with low academic self-efficacy. Specifically, several studies have found a positive relation between perceived teacher support and GPA in elementary school students (Dubow & Tisak, 1989) and secondary school students (Malecki & Elliot, 1999; Rosenfeld, Richman, & Bowen, 2000). In addition, higher perceived teacher support relates to higher teacher ratings of middle school academic competence (Malecki & Demaray, 2003) and higher standardized reading and math scores in elementary and middle school students (Klem & Connell, 2004). Despite the majority of studies finding perceived teacher support to relate to achievement-related variables, other studies have found no relation between perceived teacher support and GPA in elementary (Dubow et al., 1991) and middle school samples (Rueger, Malecki, & Demaray, 2010).

Although perceived teacher support appears to benefit the academic performance of most students, some evidence suggests that perceived teacher support may be more advantageous for students at-risk for academic failure. In Malecki and Demaray's (2006) study of middle school students, perceived teacher support was more strongly related to GPA for lower SES students than for higher SES students. Given that academic achievement strongly relates to students' SES (Caldas & Bankston, 1997; Ma, 2000; Malecki & Demaray, 2006), a plausible alternative explanation for these findings could be that perceived teacher support is more important for students who struggle academically.

Using an observational measure of teacher support instead of a child report measure, Hamre and Pianta (2005) found that by 1st grade, kindergarten students at risk for failure who were placed in classrooms with emotionally and instructionally supportive teachers developed levels of academic skills similar to low-risk peers. Indeed, teachers appear to provide more support to academically weak students (Baker, 1999; Elias & Haynes, 2008). As described in Elias and Haynes (2008), supporting the students who need the most assistance may simply reflect "teachers [doing] what they have been trained to do" (p. 489). Based on these findings, perceived teacher support may be more prevalent and important for students with low academic self-efficacy.

In contrast to the abundance of longitudinal research on the relation of academic self-efficacy to academic performance (see Pajares, 1996; Pintrich & Schunk, 2002), the majority of studies suggesting a positive relation between perceived teacher support and academic performance have been cross-sectional (Dubow & Tisak, 1989; Klem & Connell, 2004; Malecki & Demaray, 2003, 2006; Malecki & Elliot, 1999; Rosenfeld et al., 2000). The few longitudinal studies that have examined perceived teacher support as a predictor of change in academic performance have found less consistent relations. In a short-term longitudinal study across one academic year in 7th- and 8th-grade students, Rueger et al. (2010) found fall levels of perceived teacher support to be unrelated to spring GPA. Similarly, Elias and Haynes (2008) did not find a relation between fall levels of perceived teacher support and change in GPA across one academic year in 3rd-grade students, although they did find change in perceived teacher support to be related to change in GPA. Elias and Haynes's (2008) results differ from an earlier longitudinal study that found initial perceived teacher support and change in perceived teacher support to be unrelated to GPA over a two-year period (Dubow et al., 1991) in 3rd- through 5th-grade students. Given the inconsistency of results across cross-sectional and short-term longitudinal studies, further examination of perceived teacher support as a predictor of change in academic performance is needed.

Studies on perceived teacher support also have relied heavily on GPA as an indicator of academic performance. Researchers, however, have long noted that grades can be greatly influenced by factors unrelated to academic performance, such as halo effects and other heuristics and biases (e.g., Archer & McCarthy, 1988; Caldwell & Mowry, 1934). In addition, measures of social behavior were found to be robust predictors of grades with standardized test scores controlled in a study of middle school students (Wentzel, 1993). For these reasons, direct assessments of academic skills (i.e., curriculum-based measurement; CBM) may be better indicators of actual academic performance. In CBM, brief assessments of academic skills (e.g., number of words read correctly in 1 min on grade-level reading probes) are collected repeatedly to monitor student progress (see Deno, 1985; Wayman, Wallace, Wiley, Tichá, & Espin, 2007). In contrast to GPA, CBM can provide a sensitive, direct measure of skill growth in specific academic areas. Direct measures of both reading and math performance, instead of global GPA, may also be useful in investigating the contributions of academic self-efficacy and teacher support given that self-efficacy on language arts tasks appears to be more

sensitive to the classroom social environment, whereas self-efficacy on mathematics tasks appears to be more strongly related to task difficulty (McMahon, Wernsman, & Rose, 2009). Furthermore, the sensitivity of CBM to skill growth over short periods of time (Deno, Fuchs, Marston, & Shin, 2001; Fuchs, Fuchs, Hamlett, Walz, & Germann, 1993; Shin, Deno, & Espin, 2000) makes CBM particularly well-suited to investigate change in academic skills within one academic year, which is the time interval of the current study.

1.4. Current study

In summary, prior research on academic self-efficacy has insufficiently addressed the possibility that social contextual factors (i.e., perceived teacher support) could moderate the well-established relation between self-efficacy and academic performance. In addition, research on teacher support has relied heavily on GPA as an indicator of academic performance, and inconsistent relations between perceived teacher support and academic performance have been found across cross-sectional and longitudinal studies. To address these limitations, the contributions of academic self-efficacy and perceived teacher support in relation to academic skill development over the course of one academic year for 5th-grade students were investigated in the current study. We hypothesized that higher levels of academic self-efficacy would relate to greater growth in reading and mathematics across the school year (Hypothesis 1) and that academic self-efficacy would interact with perceived teacher support in relation to growth in reading and mathematics (Hypothesis 2). Consequently, Hypothesis 2 predicts that perceived teacher support would moderate the positive relation between academic self-efficacy and academic skill growth.

2. Method

Data were collected from three separate cohorts of 5th-grade students at one elementary school during the 2004–05 (7 classrooms), 2005–06, (7 classrooms), and 2006–07 (6 classrooms) academic years. Of the 193 total students who participated, 54% were girls and 14% received free or reduced school lunches. Students in the sample were 92% White, 5% Multiracial, 2% Latino, 1% Asian, and less than 1% African American, which is similar to overall school demographics. Nine percent of the participants received special education services. Specific Learning Disability (SLD; 5% of participants) and Communication Disorder (2% of participants) were the most prevalent special education classifications.

2.1. Setting

Data for the current study were drawn from a large, school-based Response to Intervention (RTI) initiative called The Academic Well-Check Program (AWCP). The AWCP (<http://education.indiana.edu/awcp>) is a school–university partnership between the School Psychology Program at a large research university in the Midwest and a local mid-sized rural school district. The AWCP consists of school psychology graduate students' advanced RTI practicum, during which they collaborate with teachers to identify struggling students using a convergence of information, including CBM scores. Once identified, graduate students and teachers work together to provide interventions and monitor student progress. In the current study, data were drawn from one of the larger elementary partner schools in the AWCP. This building serves approximately 600 students in 3rd through 5th grade. The core reading curriculum used is Houghton-Mifflin Reading (2003) and the core math curriculum is Saxon Math K–12 (2004). Struggling students with and without identified SLD in reading participate in SRA Corrective Reading (1999). Numerous additional resources are offered to struggling students, including after-school tutoring and working individually with school psychology graduate students.

2.2. Instrumentation

2.2.1. Academic self-efficacy

Greene, Miller, Crowson, Duke, and Akey (2004) developed the seven-item Academic Self-Efficacy Scale to measure the degree of confidence a student has that he or she can be successful learning at his or her current school. The wording of items was modified for the current study so that items were anchored to a 5th-grade context (e.g., "I am sure that I can do as well as, or better than, other students in 5th grade on exams."). Students

rated items on a scale ranging from 1 (*strongly disagree*) to 5 (*strongly agree*). Greene et al. (2004) reported adequate internal consistency reliability for the scale ($\alpha = .91$), and internal consistency was also acceptable in the current sample ($\alpha = .82$). The validity of the scale has been supported in studies demonstrating relations between the academic self-efficacy scale and student achievement goals and academic engagement (Greene & Miller, 1996; Greene et al., 2004).

2.2.2. Perceived teacher support

Perceived teacher support was measured by the teacher support scale of the Child and Adolescent Social Support Scale (CASSS; Malecki, Demaray, & Elliott, 2000), which assesses the four types of support (i.e., emotional, instrumental, informational, and appraisal) described in House (1981). Each of the 12 items is rated by students on the perceived frequency of a supportive behavior (1 = *never* to 6 = *always*) and on the importance that they attribute to that behavior (1 = *not important* to 3 = *very important*). As is customary in studies using the CASSS (e.g., Demaray, Malecki, Davidson, Hodgson, & Rebus, 2005; Malecki & Demaray, 2006), only the frequency ratings were analyzed in the current study. The CASSS teacher support scale (e.g., “My teacher explains things that I don’t understand.”) has good reported internal consistency ($\alpha = .88$ for 3rd- to 6th-grade students; Malecki & Demaray, 2002), with similar levels found in the current study ($\alpha = .93$). Construct validity of the CASSS is supported by evidence of its relations with measures of self-concept, social skills, and problem behavior (Malecki & Demaray, 2002).

2.2.3. Academic functioning

Academic functioning was assessed using curriculum-based measurement (CBM), a formative evaluation method that allows teachers to monitor student progress and adjust intervention accordingly (Deno, 1985). Reading and math CBM probes were obtained from AIMSweb (<http://www.aimsweb.com>), a web-based system that provides CBM assessment tools for screening students in kindergarten through 8th grade in addition to a web-based information management system to document student progress. Specific probes included Reading-CBM (R-CBM), Maze-CBM, and Mathematics-CBM (M-CBM). Probes are designed to be similar in content and difficulty so that a student’s performance can be compared over time and in relationship to end-of-year goals. Consequently, the same probes were administered at each benchmark period in the current study, which is consistent with recommended universal screening administration procedures outlined in AIMSweb (<http://www.aimsweb.com>). In addition, using the same probes for benchmarks across the academic year is supported by a study on oral reading fluency (Jenkins, Zumeta, Dupree, & Johnson, 2005) that found smaller standard errors for gain scores when the same passages were administered and minimal passage memory effects when intervals between administrations were greater than 10 weeks.

2.2.4. R-CBM

Oral reading fluency skills are measured by R-CBM probes during which students read aloud for 1 min from meaningful, connected and graded passages of text under standardized conditions. Three 5th-grade benchmark passages (5P01, 5P02, and 5P03), approximately 250–300 words in length, were administered at each benchmark assessment. R-CBM is scored as the median number of words read correctly (WRC) across three passages. During field testing of the benchmark passages, the average correlation between alternate forms was .88 across 5th-grade passages (Howe & Shinn, 2002). A recent meta-analysis of 41 studies conducted over the past 30 years found strong positive relations between R-CBM assessments and standardized tests of vocabulary, word decoding, and reading comprehension and that the relations between R-CBM scores and standardized reading assessments did not differ across 1st through 6th grade (Reschly, Busch, Betts, Deno, & Long, 2009).

2.2.5. CBM-Maze

Reading comprehension skills are measured by CBM-Maze probes during which students complete a multiple-choice cloze task while reading silently for 3 min (Shinn & Shinn, 2002b). The first sentence of a 150–400 word passage is left intact. Thereafter, every seventh word is replaced with three words inside parenthesis, one being correct and the other two being distracters. For example, sentences are structured as follows: “The third and youngest (once, daughter, gate) was quite different from the other (him, two, beast).” CBM-Maze is scored for correct maze choices (CMC). One CBM-Maze probe (5P01) was administered at each benchmark. If students complete the task in less than 3 min, scores are prorated; however, no students finished probes in less than 3 min, so no scores were prorated in this study. The Maze

task provides reasonable evidence for alternate-form reliability across 1 to 3 month intervals ($r = .80$; Shin et al., 2000) as well as criterion-related validity with R-CBM ($r = .77$ to $.86$ for 3rd through 5th grade; Espin, Deno, Maruyama, & Cohen, 1989).

2.2.6. M-CBM

Math computation skills are measured by M-CBM probes, which can be administered to students individually or in small and class-size groups (Shinn, 2004). M-CBM probes are administered for 2 to 4 min depending on the grade-level of the assessment materials. Fifth-grade students have 4 min to complete as many problems as possible. One M-CBM probe (5P01) was administered at each benchmark assessment. M-CBM probes are scored by counting the number of Correct Digits (CD) the student writes. For students in 3rd through 5th grade, estimates of alternate-form reliability ranged from $.72$ to $.93$, with most values above $.80$ (see Foegen, Jiban, & Deno, 2007, for a review). Validity estimates using a variety of criterion measures (e.g., California Achievement Tests: Math Computation, CTB/McGraw-Hill, 1992; Wide Range Achievement Test, Revised: Math Computation, Jastak & Wilkinson, 1984) have ranged from moderate ($r = .35$) to strong ($r = .87$).

2.3. Procedure

The third author and a graduate assistant collected academic self-efficacy and teacher support data during May 2005, 2006, and 2007. The self-report surveys were administered in the classroom at a time designated by the teacher. Each student received a packet with the self-report surveys and a manila folder. Students were instructed to use the manila folder to cover their surveys and maintain privacy as they answered the questions. All items were read aloud (to guard against differing reading proficiencies), and students completed each item individually as the whole group worked through the same items.

R-CBM, CBM-Maze, and M-CBM data were collected in September, January, and May of each year by teachers as part of the school's standard benchmark periods (i.e., fall, winter, and spring). R-CBM probes were individually administered, whereas CBM-Maze and M-CBM probes were group administered. Fifth-grade teachers participated in AIMSweb (<http://www.aimsweb.com>) training during which administration and scoring procedures were covered. Training included exercises to ensure high implementation fidelity (e.g., scoring and review of the Accuracy of Implementation Rating Scale; Shinn & Shinn, 2002a) to detect procedural errors and scoring of inter-observer agreement (IOA) during training activities. Training continued until teachers' IOA with the trainer was greater than 90%, but IOA data were not collected during the R-CBM, CBM-Maze, and M-CBM benchmark assessments.

2.4. Data analytic plan

2.4.1. Formation of latent constructs

Prior to conducting analyses related to study hypotheses, several analyses were conducted to support the representation of academic self-efficacy (ASE) and perceived teacher support (PTS) as latent variables in subsequent analyses. So long as scales are unidimensional and the goal of the study is to investigate structural relations among constructs, the representation of ASE and PTS as latent constructs measured by item parcels (averaged subsets of items) maintains the benefits of latent variable analysis (i.e., representation of measurement error, prevention of attenuation of structural coefficients) without unnecessarily increasing the complexity of the analysis by including individual items as indicators (Coffman & MacCallum, 2005; Little, Cunningham, Shahar, & Widaman, 2002). To support this approach, exploratory factor analysis of the ASE and PTS scales with an iterative estimator (i.e., maximum likelihood) and an oblique rotation, as recommended in Little et al. (2002), was reported to investigate the dimensionality of the scales. Following analyses of dimensionality, confirmatory factor analyses were conducted with ASE and PTS represented as latent constructs measured by parceled indicators to support their inclusion in subsequent structural equation models to address study hypotheses.

2.4.2. Growth models

Next, two growth models were fit for each academic performance measure (i.e., R-CBM, CBM-Maze, and M-CBM) to characterize overall patterns of change and to provide variance parameters useful in

subsequent effect size calculations. The first model included only random intercepts (i.e., the unconditional means model; Singer & Willett, 2003), and they are specified in the following equations:

$$\text{Level 1: } Y_{ti} = \pi_{0i} + e_{ti}$$

$$\text{Level 2: } \pi_{0i} = \gamma_{00} + \zeta_{0i}$$

where Y_{ti} is the CBM score of individual i at occasion t , π_{0i} is the average CBM score for person i across occasions, γ_{00} is the grand mean (i.e., the average across all participants) across all measurements, ζ_{0i} is a residual representing the deviation of an individual's average from the grand mean, and e_{ti} is a residual representing the deviation of an individual's score at one occasion from the average score for that individual.

The second model included both random intercepts and slopes (i.e., the unconditional growth model; Singer & Willett, 2003), as presented in the following equations:

$$\text{Level 1: } Y_{ti} = \pi_{0i} + \pi_{1i} \text{TIME}_{ij} + e_{ti}$$

$$\text{Level 2: } \pi_{0i} = \gamma_{00} + \zeta_{0i}$$

$$\pi_{1i} = \gamma_{10} + \zeta_{1i}$$

which, as compared to the unconditional means model, adds the terms π_{1i} to represent the average linear change over time; TIME_{ij} (coded as 0 for the fall assessment, 1 for the winter assessment, and 2 for the spring assessment) to center the model at the fall assessment and to scale the linear growth factor as the amount of linear change per benchmark period; γ_{10} to represent the mean linear change for all participants; and ζ_{1i} to represent an individual's deviation from the average linear change for all participants.

2.4.3. Hypothesized models

To examine Hypothesis 1 (i.e., the extent to which ASE and PTS relate to change in CBM scores), the latent ASE and PTS factors (as measured by three item parcels each) were included as predictors of the random intercepts and slopes (π_{0i} and π_{1i}) of the growth models for each academic performance measure in separate analyses. In addition, possible interactions between ASE and PTS (Hypothesis 2) were tested by including a latent interaction term as an additional predictor of the random intercepts and slopes (see Fig. 1). The latent interaction was estimated directly using maximum likelihood using the latent moderated structural equations (LMS) approach of Klein and Moosbrugger (2000). The LMS method has performed well relative to other approaches to calculate latent interactions, such as including multiplied indicators as additional observed variables in the analyses (Little, Bovaird, & Widaman, 2006; Marsh, Wen, & Hau, 2004). Regression weights (b) are unstandardized; consequently, they should be interpreted as the amount that fall CBM scores go up or down per unit of change in the predictor (for predictors of intercepts) or the amount that linear slope (i.e., the amount of change in CBM per benchmark period, e.g., fall to winter) increases or decreases per one point change in the predictor (for predictors of slopes). Descriptive statistics for all study variables will be presented to facilitate the interpretation of these coefficients. Pseudo- R^2 calculations are presented as measures of effect size, reflecting the percentage reduction in variance of the random intercepts or with the addition of the predictors (Singer & Willett, 2003).

All analyses were conducted in Mplus 5.21 (Muthén & Muthén, 2007) using the robust maximum likelihood estimator, which accounts for non-normality of indicators. To address the nesting of students within classes in this study, tests of statistical significance were corrected by adjusting standard errors using the COMPLEX command in Mplus.¹

¹ Although the COMPLEX command adjusts standard errors for non-independence, COMPLEX does not adjust regression coefficients, and analyses can be biased to the extent that regression coefficients reflect correlations between group-level vs. individual-level variables. The extent of this bias in the current study appears to be minimal, however, as evidenced by the low intra-class correlations for the academic self-efficacy ($ICC = .006$) and perceived teacher support ($ICC = .062$) factors. Design effects related to nesting of students in classrooms were 1.06 for academic self-efficacy and 1.58 for perceived teacher support, and both values are below the recommended cutoff of 2.00 that would indicate substantial violations of independence (Peugh, 2010).

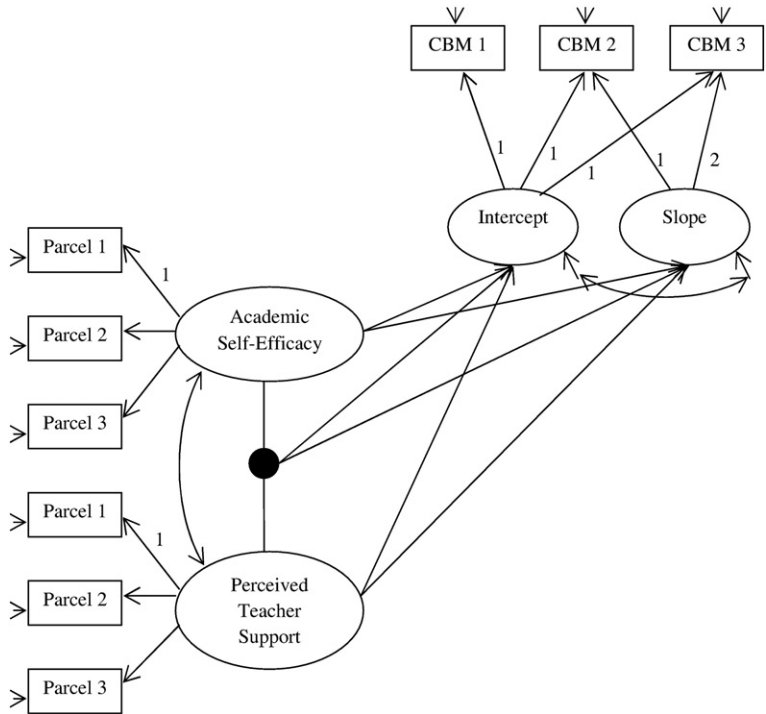


Fig. 1. Structural diagram for predictive models testing academic self-efficacy and perceived teacher support as predictors of CBM scores. The latent interaction term is depicted as a filled circle.

3. Results

The results section is organized into four sections, of which two sections address preliminary analyses (i.e., the measurement of academic self-efficacy [ASE] and perceived teacher support [PTS] and the fitting of growth models for the academic performance measures) and two sections report tests of study hypotheses regarding the relations between change trajectories of academic performance, ASE, and PTS. Descriptive statistics (*Ms* and *SDs*) for all study variables are presented in Table 1. In reference to overall levels of

Table 1
Descriptive statistics.

Variable	<i>M</i>	<i>SD</i>
Academic self-efficacy (Parcel 1)	4.01	.73
Academic self-efficacy (Parcel 2)	4.31	.61
Academic self-efficacy (Parcel 3)	4.48	.55
Perceived teacher support (Parcel 1)	4.82	1.04
Perceived teacher support (Parcel 2)	4.89	.95
Perceived teacher support (Parcel 3)	4.61	1.13
R-CBM (Fall)	124.81	36.68
R-CBM (Winter)	136.60	38.63
R-CBM (Spring)	146.07	38.82
CBM-Maze (Fall)	19.13	7.67
CBM-Maze (Winter)	23.54	8.55
CBM-Maze (Spring)	26.53	7.77
M-CBM (Fall)	54.96	19.56
M-CBM (Winter)	52.87	20.01
M-CBM (Spring)	76.90	26.19

academic skills, 49%, 60%, and 83% of the sample met or exceeded the AIMSweb (<http://www.aimsweb.com>) target scores for R-CBM, CBM-Maze, and M-CBM, respectively, at the spring of 5th-grade benchmark.

3.1. Formation of latent ASE and PTS constructs

Results of the exploratory factor analyses suggested that both the ASE and PTS scales were unidimensional. For the ASE scale, one factor emerged (first eigenvalue = 3.43, second eigenvalue = .91) that explained 49% of the variance in the seven items. The factor loadings ranged in value from .48 to .72 ($M = .63$). In reference to the PTS scale, one factor also emerged (first eigenvalue = 6.84, second eigenvalue = .86) that explained 57% of the variance in the 11 items.

Three parcels were created for each scale by randomly assigning items to parcels. To evaluate fit and calculate the reliability of the constructs with item parcels as indicators, a model was fit with the ASE and PTS factors loading on the three parcels corresponding to each factor with the factors allowed to covary. Overall model fit was excellent, $\chi^2(8) = 7.90$, $p = .44$; CFI = 1.00, RMSEA = .000. Factor loadings were of large magnitude on the ASE (range = .77 to .81) and PTS (range = .85 to .96) parcels, yielding composite reliability estimates (Fornell & Larcker, 1981) of .90 and .95, respectively. The correlation between the ASE and PTS factors was positive, of moderate magnitude, and statistically significant ($r = .31$, $p < .001$).

3.2. Growth models

On R-CBM, the unconditional growth model fit significantly better than the unconditional means model, $\chi^2(3) = 231.80$, $p < .001$, indicating that the model estimating individual rates of change fit better than the model assessing only overall individual differences in average R-CBM. Inspection of growth model parameter estimates (π_{0i} and π_{1i}) indicates that on average students read 124.68 WRC ($SD = 36.22$) in the fall and increased by an average of 10.94 WRC ($SD = 6.70$) per benchmark period (i.e., fall to winter and winter to spring). The variances of the intercepts (1311.92, $p < .001$) and slopes (44.95, $p = .01$) were statistically different from zero, indicating that fall scores and linear growth varied across students. The near-zero correlation between π_{0i} and π_{1i} ($r = -.004$, $p = .97$) indicates that students' linear change on R-CBM was unrelated to their R-CBM scores at the fall benchmark. On CBM-Maze, the unconditional growth model fit better than the unconditional means model, $\chi^2(3) = 106.10$, $p < .001$. The growth parameter estimates suggest that students on average completed 19.03 CMC ($SD = 7.50$) in the fall and increased on average by 3.79 CMC ($SD = 2.53$) per benchmark period. The variance estimate was statistically different from zero for the intercepts (56.20, $p < .001$) but not slopes (6.42, $p = .21$), indicating that fall scores but not linear growth varied substantially across students. The correlation between π_{0i} and π_{1i} ($r = -.29$, $p = .34$) was not statistically significant for CBM-Maze, indicating no relation between fall benchmark values and amount of change. On M-CBM, the unconditional growth model also fit better than the unconditional means model, $\chi^2(3) = 59.24$, $p < .001$, with students obtaining 52.76 CD ($SD = 15.22$) in the fall and increasing by 10.12 CD ($SD = 8.57$) on average. The variance estimate was statistically different from zero for the intercepts (231.93, $p = .002$) but not slopes (73.48, $p = .11$), indicating that fall scores but not linear growth varied substantially across students. The correlation between π_{0i} and π_{1i} ($r = -.22$, $p = .49$) was not statistically significant.

3.3. Hypothesized models

The results of all analyses are presented in Table 2. For the R-CBM model, only ASE explained a significant amount of unique variance in fall scores ($b = 24.51$, $p < .001$), indicating that students with higher initial R-CBM scores reported higher concurrent levels of ASE. Specifically, a prototypical student with 1 SD higher than average ASE read at 138 WRC at the fall benchmark; in contrast, a student with 1 SD lower than average ASE read at 110 WRC. Neither ASE nor PTS explained unique variance in linear change on R-CBM. There was no evidence of interaction between ASE and PTS in relation to fall R-CBM scores or linear change in R-CBM. Based on the value of pseudo- R^2 for the random intercepts, ASE explained 15% of the variance in fall R-CBM scores.

Similar results were found for the CBM-Maze model. Only ASE explained unique variance in fall scores ($b = 5.21$, $p < .001$). To interpret, a prototypical student at +1 SD on ASE answered 22 CMC during the fall benchmark, and a student at -1 SD on ASE answered 16 CMC. Neither ASE nor PTS explained variance in

Table 2
Academic Self-Efficacy And Perceived Teacher Support As Predictors Of CBM Growth Parameters.

Measure	Predictor	Dependent variable			
		Intercepts		Slopes	
		B	SE	b	SE
R-CBM	ASE	24.51 ***	4.52	1.18	0.77
	PTS	−3.03	3.43	−0.88	0.62
	ASE × PTS	2.92	3.59	0.06	0.80
CBM-Maze	ASE	5.21 ***	0.96	−0.59	0.38
	PTS	−0.64	0.74	0.01	0.30
	ASE × PTS	0.67	0.64	−0.08	0.70
M-CBM	ASE	9.55 ***	2.89	1.72	1.11
	PTS	0.16	1.74	−2.93 *	1.36
	ASE × PTS	1.97	3.54	−2.90 *	1.38

Note. Regression weights (*b*) are unstandardized. ASE = academic self-efficacy. PTS = perceived teacher support.

* $p < .05$.
*** $p < .001$.

linear change on CBM-Maze, and no interactions between ASE and PTS were found in the CBM-Maze analyses. In reference to effect size, ASE explained 21% of the variance in fall CBM-Maze scores.

For the M-CBM model, only ASE explained unique variance in fall scores ($b = 9.55, p < .01$). As an interpretive example, a prototypical student with 1 SD higher than average ASE completed 58 CD at the fall benchmark; in contrast, a student with 1 SD lower than average ASE completed 47 CD. Regarding linear change in CD, a statistically significant interaction was found between ASE and PTS ($b = -2.90, p < .05$). In Fig. 2, the CD trajectories, based on the M-CBM model parameter estimates, for prototypical students at various levels of ASE and PTS are presented to facilitate the interpretation of the interaction term. As displayed in the figure, linear change in M-CBM scores per benchmark period was greater for students with

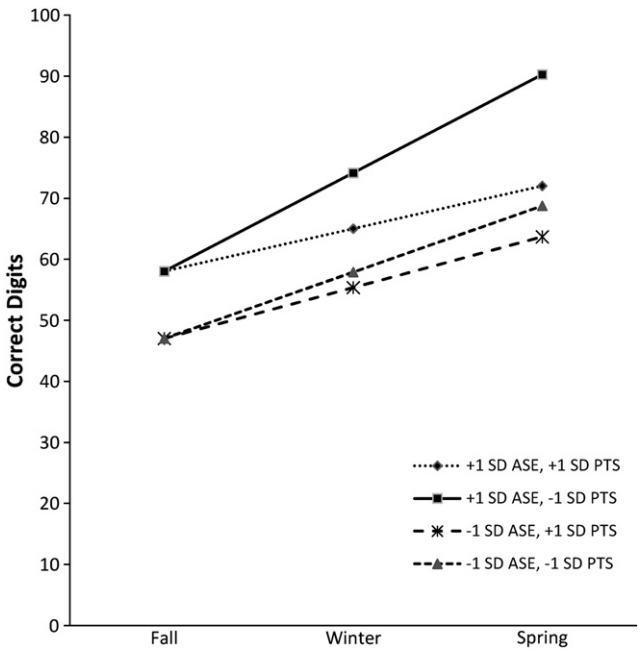


Fig. 2. Trajectories of change on M-CBM at varied levels of academic self-efficacy and perceived teacher support. ASE = academic self-efficacy. PTS = perceived teacher support.

low levels of PTS. At -1 SD PTS, a student increased by an average of 13.50 CD per benchmark period. In comparison, a student reporting $+1$ SD PTS changed by an average of 7.66 CD per benchmark period. Among students with low levels of PTS, the greatest linear change was for students who also reported high levels of ASE. Specifically, a student -1 SD on both ASE and PTS changed by an average of 16.12 CD per benchmark period, whereas a student -1 SD on ASE and $+1$ SD on PTS changed by an average of 10.87 CD. Regarding the magnitude of these relations, ASE explained 6% of the variance in fall M-CBM scores, and the combined predictors explained 3% of the variance in linear change in M-CBM scores.

3.4. Heterogeneity of change trajectories

To further explore ASE and PTS in relation to patterns of change on the CBM scores, students were grouped based on their change trajectories on the CBM scores (i.e., values of intercepts and slopes), as detailed below. Then, differences between the trajectory groups on ASE and PTS were examined.²

To form trajectory groups, low and high skill groups were identified on each CBM probe by selecting students that scored in the bottom and top 25% of the sample on the fall benchmarks, as determined by random intercepts values from the growth models. The low and high skill groups then were divided further into small and large growth groups, which were determined by rank-ordering students in each skill group based on the amount of linear change on each CBM probe (i.e., random slope values). This process yielded four groups ($n = 24$) for each CBM probe: (a) Low Skill/Small Growth, (b) Low Skill/Large Growth, (c) High Skill/Small Growth, and (d) High Skill/Large Growth.

Following trajectory group assignment, differences in ASE and PTS, as represented by standardized average scores on the measures, between the small and large growth groups within each initial skill group were tested in a series of independent samples *t*-tests. Statistical power is limited for these comparisons given the small group sizes (i.e., the chances that an effect size of $d = .5$ would be detected as statistically significant are 40%); consequently, standardized mean difference effect sizes (d) are reported and emphasized when appropriate. The means and standard deviations of ASE and PTS for each group are presented in Table 3.

On R-CBM, there were no statistically significant differences on ASE and PTS between the Low Skill/Small Growth and Low Skill/Large Growth groups or the High Skill/Small Growth and High Skill/Large Growth groups. A medium to large difference in PTS ($d = .46$) was present between the Low Skill/Small Growth and Low Skill/Large Growth groups, with the Low Skill/Small Growth group reporting higher levels of PTS. On CBM-Maze, a statistically significant difference on ASE was found between the Low Skill/Small Growth and Low Skill/Large Growth groups ($t = 2.25$, $p = .03$, $d = .65$), with the Low Skill/Small Growth group reporting higher levels of ASE. No other statistically significant or large magnitude differences were found among the growth groups on CBM-Maze.

On M-CBM, a large and statistically significant difference on PTS was found between the Low Skill/Small Growth and Low Skill/Large Growth groups ($t = 4.66$, $p < .001$, $d = 1.35$), with the Low Skill/Small Growth group reporting higher levels of PTS. Other contrasts between the M-CBM growth groups were not statistically significant and of small magnitude. Due to the small group sizes for the comparisons, these results should be interpreted with caution; however, the general pattern of results appears largely consistent with the prior, variable-centered findings that students with the strongest initial academic skills reported the highest levels of ASE and offers additional evidence that students with the most academic difficulties (i.e., smallest growth) reported higher levels of perceived teacher support.

4. Discussion

In order to better understand the relations between perceived teacher support, academic self-efficacy and academic performance, this study used direct academic skill assessments (i.e., CBM probes) to measure

² This group of results can be conceptualized as exploratory person-oriented analyses (Bergman & Magnusson, 1997) to complement the variable-oriented analyses already presented. We realize that (a) the analysis does not provide unique statistical information beyond the primary analyses and (b) the extreme groups approach has limitations (Preacher, Rucker, MacCallum, & Nicewander, 2005); however, we believe that these analyses aid readers in conceptualizing how the primary study variables relate at different levels of academic performance. We fully recognize that the method to assign students to trajectory groups is arbitrary; however, the overall pattern of results was robust to assignment method (e.g., quintiles instead of quartiles) and analysis method (e.g., growth mixture modeling).

Table 3

Characteristics of CBM trajectory classes.

Measure	Group	ASE		PTS	
		<i>M</i>	<i>SD</i>	<i>M</i>	<i>SD</i>
R-CBM	Low skill/Small growth	−0.24	0.54	0.33	0.76
	Low skill/Large growth	−0.10	0.46	−0.11	1.14
	High skill/Small growth	0.35	0.35	0.35	0.82
	High skill/Large growth	0.32	0.41	0.06	0.90
CBM-Maze	Low skill/Small growth	−0.14	0.40	−0.14	1.12
	Low skill/Large growth	−0.47	0.58	−0.02	1.26
	High skill/Small growth	0.38	0.32	0.28	0.68
	High skill/Large growth	0.38	0.38	0.11	0.83
M-CBM	Low skill/Small growth	−0.29	0.54	0.57	0.59
	Low skill/Large growth	−0.20	0.47	−0.83	1.34
	High skill/Small growth	0.35	0.37	0.25	0.86
	High skill/Large growth	0.30	0.37	−0.04	0.81

Note. Values of academic self-efficacy (ASE) and perceived teacher support (PTS) are standardized to facilitate interpretation.

the within-year growth in reading and mathematics among three cohorts of 5th-grade students. Assessing academic performance in this manner was thought to provide a more sensitive measure of change and valid indicator of skill development than GPA, which has been frequently utilized in previous research. We hypothesized that higher levels of academic self-efficacy and perceived teacher support would be related to fall performance as well as growth in reading and mathematics across the school year.

Across all three academic areas measured in this study, academic self-efficacy was associated with academic performance at the beginning of the school year. Students reporting higher academic self-efficacy demonstrated the strongest academic skills. This result likely reflects such students' success with prior learning and school experiences, which contributes to their perceptions about skills and ability to perform well on future tasks (Pajares, 1996; Pintrich & Schunk, 2002). In contrast to a longitudinal study finding reciprocal relations between academic self-concept and academic achievement (Marsh & O'Mara, 2008), academic self-efficacy did not explain unique variance in academic skill growth, possibly due to the short time interval (i.e., one academic year) of the current study.

The relation of perceived teacher support appears more complex and current findings differ from those of previous studies. In the current study, perceived teacher support did not uniquely relate to initial fall performance or growth over the year for any of the academic areas. Previous research on this topic is somewhat inconsistent with some short-term longitudinal studies reporting no relation (Dubow et al., 1991; Rueger et al., 2010), one cross-sectional study reporting a stronger relation for students of low SES (Malecki & Demaray, 2006), and another short-term longitudinal study reporting a relation specifically between change in teacher support over time and change in GPA (Elias & Haynes, 2008).

In the current study, academic self-efficacy interacted with perceived teacher support in relation to math skill growth. In general, lower levels of teacher support were associated with greater growth in math skills, and this trend was most evident among students with high academic self-efficacy. Given the strong relation between academic self-efficacy and fall CBM scores found in this study, one explanation could be that high-achieving students did not appear to need high levels of perceived teacher support to maintain high rates of academic skill growth. Specifically, the students who needed the least amount of assistance (i.e., high achievers with high growth rates) reported lower levels of perceived support, which is what one would expect if teachers are assisting the students most in need (i.e., low achievers with low growth rates). Given that perceived teacher support was measured by student report instead of directly observed, it is possible, however, that high-achieving students underestimate the extent that they receive teacher support due to their high academic self-efficacy.

To further investigate patterns of perceived teacher support, exploratory analyses examined perceived teacher support across groups of students defined by levels of initial academic performance and growth over time. On both the oral reading fluency (R-CBM) and mathematics (M-CBM) probes, students who began the school year with low skills (bottom 25%) and made small amounts of growth reported higher levels of perceived teacher support than those with similar initial skills yet more growth over time. These

findings may be related to a decrease in continued teacher intervention over time as initially struggling students demonstrated progress. Although these findings are preliminary, it does provide evidence of “teachers [doing] what they have been trained to do” (Elias & Haynes, 2008, p. 489), which is supporting the students most in need (i.e., low achieving students who are making limited progress).

Why might these results differ from prior studies that found a relation between teacher support and academic performance? First, the academic performance measures used in the study were part of the school's RTI model to address academic concerns (e.g., Fuchs, Mock, Morgan, & Young, 2003); consequently, teachers had timely information regarding student performance, and low-achieving students received more teacher instructional support via small group and individualized academic interventions. Second, the measures of academic performance (CBM) used in the study differ from prior studies that have relied on GPA as an academic indicator, and CBM is better able to detect skill growth than GPA and less subject to halo effects and other heuristics and biases (e.g., Archer & McCarthy, 1988; Caldwell & Mowry, 1934). In sum, it is possible that benchmarking and progress monitoring students' academic skills better enables teachers to support the students most in need.

4.1. *Study limitations*

There are several limitations of this study that must be considered. First, perceived teacher support and academic self-efficacy were assessed at one point in time (i.e., May of each academic year). The timing of this rating may have impacted the findings related to initial academic performance in the fall. It is possible that fall academic performance is more strongly associated with perceptions of support from the previous year's teacher. In fact the change in, not the static level of, perceived levels of support is a significant variable in adolescents' social-emotional adjustment (Cornwell, 2003).

Second, perceived teacher support and academic self-efficacy were assessed by single, student-reported measures. It is possible that socially desirable responding could explain reports of greater perceived teacher support among lower achieving students given that children with lower measured intelligence and academic achievement tend to score higher on measures of social desirability (Crowne, 1979; Evans & Forbach, 1982). Although this limitation is typical of studies on perceived teacher support and academic self-efficacy, the current study could have been strengthened by the inclusion of multiple measures from multiple informants. Nonetheless, in the current study, we were interested in students' subjective, self-reported perceptions of their experience with teacher support and academic self-efficacy. Furthermore, the measure of academic self-efficacy was global (i.e., across all academic subjects) rather than domain specific (i.e., regarding reading and math); consequently, different results may have been obtained if domain specific measures of academic self-efficacy were used.

Third, although teachers were trained to criterion (>90% accuracy) in the scoring of CBM probes, information regarding the accuracy of their scoring over the course of the academic year was not available. This limitation is a byproduct of using academic benchmark data that was already being collected by teachers as part of the school's three-tier intervention program. Using the school's existing data introduces a possible confound that the teachers were aware of students' scores and likely modified their behavior toward students based on these scores (i.e., provided students group and individualized academic interventions), and this study would have benefitted from collection of IOA data on the CBM probes over the course of the academic year to facilitate reliability calculations and to improve statistical conclusion validity.

An additional potential confound is related to teachers being aware of students' scores on the academic performance measures. Preliminary analyses for the current study found that linear change in R-CBM (i.e., slopes) was unrelated to fall scores (i.e., intercepts), which is in contrast to extensive existing research evidence (e.g., Deno et al., 2001). This finding may reflect the effectiveness of the interventions that struggling students were receiving which may have increased their growth. Consequently, the provision of academic interventions for students with low fall benchmark scores may have attenuated the relation between CBM intercepts and slopes, and results may not generalize to schools without a well-implemented academic RTI program.

4.2. *Implications for practice*

The finding that students reporting high levels of academic self-efficacy experienced high levels of academic skill growth despite lower levels of perceived teacher support has implications for practice. Specifically, RTI

models for academic concerns (e.g., Fuchs et al., 2003) are designed to provide more academic support to students with weaker academic skills, and it appears that academic growth of high-achieving students may be robust despite greater teacher attention being directed to low-achieving students. Consequently, the concern that RTI protocols may cause teachers to be too focused on struggling students at the expense of higher-achieving students may be overstated (e.g., Fisher, 2009).

This finding, however, should not be interpreted to indicate that teacher support is unimportant to high-achieving students or that RTI cannot be broadened to specifically address the needs of high-achieving students (see Coleman & Hughes, 2009). Many studies document the importance of positive teacher–student relationships on student social, emotional, and academic skill development (see Hamre & Pianta, 2006), and it is possible that the measure of perceived teacher support used in this study does not capture all aspects of teacher support that are important for students. For example, Rudasill, Gallagher, and White (2010) found that students in 3rd-grade classrooms with higher observed levels of teacher emotional support performed better on standardized reading and math assessments and that teacher emotional support moderated relations between children's levels of temperamental attention and academic achievement. In addition, Malecki and Demaray (2003), using subscales of the same measure of social support used in the current study, found that student perceptions of teacher emotional support, in comparison to instrumental, informational, and appraisal support, were most strongly related to teachers' ratings of student social skills and academic competence; however, due to the very high correlations among the subscales of the support measure used in the current study, variability among the relations between academic growth and specific types of support was not evident in this study.

4.3. Future directions

In the current study, exploratory analyses investigated perceived teacher support and patterns of academic performance (initial levels and growth), and additional research is needed to confirm the finding that teachers were perceived as providing more support to students struggling academically. As mentioned previously, this line of research holds significant potential for better understanding the impact of focused intervention efforts on variables beyond academic skills (e.g., perceptions of social support). Future research in this area would benefit both the literature on social support and RTI efficacy. However, such research should also include variables related to intervention support and delivery, such as group size, characteristics of the interventionists, and the frequency and duration of interventions, so that more information regarding the actual supports provided to students is available. This line of research could further elucidate if teachers are, in fact, supporting the students most in need and if these efforts have broader implications for students' social and emotional functioning.

Future research should also investigate the relations between change in levels of perceived and actual social support and academic self-efficacy across the academic year and if these changes parallel academic skill growth. Additionally, the measurement of perceived teacher support could be improved by assessing teachers' perceptions of the extent to which they support students and completing observations of supportive teacher behaviors in addition to assessing students' perceptions of teacher support. Conducting such enhanced research in schools implementing RTI would provide unique opportunities to further explore the relations between social support and academic performance.

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